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Tony Caporale
University of Dayton, tcaporale1@udayton.edu

Barbara McKiernan
Ohio University - Main Campus

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The Fischer Black Hypothesis: Some Time-Series Evidence

Tony Caporale* and Barbara McKiernan

We estimate an ARCH-M model to analyze the relationship between the conditional standard deviation of real gross national product (GNP) and its growth rate for the period 1871–1993. We find that variability significantly increases output growth rates. In addition, impulse response functions show that the effect of variability on growth rates is dynamic. These results provide evidence in favor of Black's (1987) business cycle hypothesis.

1. Introduction

Traditionally, there has been a dichotomy in macroeconomics such that fluctuations in output are explained by business cycle models and long-run trends in output by growth models. However, it has been understood since Solow (1957) that technology shocks are an important source of output variation as well as a cause of changes in long-run growth rates (Plosser 1989). Recently, this separation in analysis has been critically reexamined. For example, Mirman (1971) and Black (1987) argue that there should be a positive relationship between volatility and growth. In contrast, Woodford (1990), Bernanke (1983), and Pindyck (1991) argue that there should be a negative relationship.

This paper empirically investigates the relationship between volatility and growth using annual U.S. data from the period 1870–1993. We find, using an ARCH-M model, a significant and positive link between output variability and economic growth over the full sample. Furthermore, impulse response functions reveal a dynamic relationship between variability and growth rates.

2. Variability and Growth

The relationship between output's trend and its variability has been the subject of intense scrutiny. For example, neoclassical economists have argued that stochastic variations in technology can have permanent effects on the path of output (see, e.g., Nelson and Plosser 1982; Long and Plosser 1983). In contrast, we examine the impact of output volatility on the growth rate of output.

There has been no theoretical consensus on the relationship between growth rates and output variability. In contrast to a traditional view of the business cycle, Black (1987) argues

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* Department of Economics, Ohio University, Athens, OH 45701, USA; E-mail caporale@ouvaxa.cats.ohiou.edu.

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that there is a positive relationship between output variability and growth. He argues that economies face a positive trade-off between risk and return in their choice of aggregate technologies as economic agents choose to invest in riskier technologies only if expected rates of return (growth rates) are high enough to compensate for the associated greater risk. Mirman (1971) gives another explanation for a positive relationship: Higher volatility will lead to greater savings (through the precautionary motive) and therefore to a higher rate of investment. If there is a positive relationship between investment and growth, growth will also increase.

Another possibility is that of no relationship between variability and growth. Traditional trend-stationary theories of macroeconomic fluctuations view deviations of output from a (nonstochastic) trend rate of growth as independent of the long-run growth rate. This is implicit in Friedman's (1968) model of the business cycle, in which movements of output away from its "natural" rate are caused by price level misperceptions. Because these deviations are triggered by monetary shocks, they in no way affect the natural rate of output growth, which depends on skills, technology, and other real factors.

Finally, output variability may lower growth rates. Large swings in economic activity could make the returns to investment riskier, which would lower the level of investment and therefore growth. This view, which stresses the importance of entrepreneurial expectations, can be traced at least as far back as Keynes (1936) and has recently been revived in the literature on sunspot equilibria (Woodford 1990). Bernanke (1983) and Pindyck (1991) suggest that the existence of irreversibilities in investment at the firm level will result in an inverse relationship between volatility and investment. Ramey and Ramey (1991) argue that this in turn will lead to lower growth rates in the aggregate. In both a sample of 92 countries and a sample of OECD nations, they find that economies with higher volatility have lower growth. Furthermore, they find that government-spending-induced volatility is also negatively related to growth.

Additional empirical evidence of a negative relationship is found in Zarnowitz and Moore (1986), who separate U.S. output from the period 1903–1981 into six subperiods, each including two to four complete business cycles. They show that average annual growth rates in real gross domestic product (GDP) are generally the highest in subsamples when the standard deviation of output is relatively low.

Evidence of a positive influence of output variability on growth is found in the cross-national studies by Kormendi and Meguire (1985) and Grier and Tullock (1989). To test Black's hypothesis, Kormendi and Meguire measure the risk of aggregate technology for a country using the standard deviation of the growth of real output. They find that the data reveal a positive risk-return trade-off such that a 1% higher average growth rate is associated with a 2% increase in the standard deviation of the growth rate. Grier and Tullock (1989), using a pooled cross-section/time series on 113 countries, also find a positive relationship between variability and growth rates while controlling for a variety of other influences.

3. Model and Results

This study differs from previous ones by using a very long time series to investigate the relationship between volatility and growth. The sample period provides an excellent laboratory setting in which to study the relationship between output variability and growth rate because it covers a period of very high growth rates and contains several periods of dramatic output volatility. These include the panic of 1907 and the Great Depression.

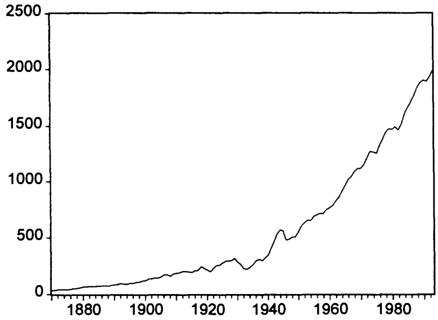

Figure 1. Real GNP (1870–1993)

We use an ARCH-M model to investigate the relationship between growth rates and volatility. ARCH models provide consistent estimates of the time-varying conditional variance of output. An ARCH-M model allows the conditional variance of output growth to appear as a regressor in the output equation.[1] A problem with employing this methodology is that ARCH effects are likely to be stronger in high-frequency time series. In fact, Baillie and Bollerslev (1989) show, using exchange rate data sampled on weekly, biweekly and four-weekly frequencies, that whereas ARCH effects are strong in weekly data, they disappear in four-weekly data. However, this is not a problem with periodicity per se. Rather, it is a function of obtaining fewer observations, and therefore a smoother series, with lower-frequency data derived from a given sample length. The averaging implicit in lower-frequency data masks the pattern in the conditional variance.

However, an appropriate test of the real technological trade-off in a hypothesis such as Black's (1987) would use low-frequency data. For example, one would not interpret a positive relationship between output variability and growth in monthly data as evidence in favor of Black's hypothesis because there would not be enough time to invest in new capital. Therefore, we use 123 years of annual data both to model the temporal relationship in Black's theory and to reveal the ARCH in the data.[2]

The data set used in this study are annual GNP in 1972 dollars for the period 1870–1993. The data from the period 1870–1946 are obtained from Gordon (1986). The postwar series is obtained from the CITIBASE economic data base.[3] Figure 1 graphs the data for the full sample. The growth rate of the series (GY) is computed by taking the difference in the logs. We estimate the best-fitting time-series (ARMA) model for the growth rate of real GNP, and the ARMA(1,2) model provides the best fit. Our model includes a dummy variable (W4246) for the period 1942–1946. Higgs (1992) explains that traditional measures of macroeconomic performance are statistically inaccurate because the United States had a command economy during this period. However, World War I does not present a problem because it had a relatively minor impact on the U.S. economy and does not distort traditional output measures.

[1] For a survey of the use of conditional variance models in finance, see Bollerslev, Chou, and Kroner (1992). For a recent application of ARCH modeling in macroeconomics, see Grier and Perry (1993).

[2] When the data are split into pre– and post–World War II blocks, all ARCH effects disappear, as expected. Because the theory implies the use of low-frequency data and ARCH effects in such data are found only in very long samples, we are prevented from using smaller subsamples in our analysis.

[3] Results similar to those presented in this paper are obtained by combining Romer's (1989) prewar GNP estimates with postwar data. Additionally, similar results are generated using annualized rates of industrial production growth from Miron and Romer (1990) with postwar rates of annualized industrial production.

The results are presented below for the period 1871–1993 (t-statistics are in parentheses):

$$\underset{(4.82)}{GY_t = .03} - \underset{(-2.32)}{.46AR(1)} + \underset{(3.85)}{.75MA(1)} + \underset{(2.95)}{.25MA(2)} - \underset{(-0.41)}{.01W4246_t}, \tag{1}$$

where adjusted R^2 = .08 and log likelihood = 184.83. A Ljung-Box Q-test is used to check for serial correlation up to 6 lags. The computed value of 5.08 rejects the presence of serial correlation at the 0.05 level. However, there is significant conditional heteroskedasticity in the data. A Lagrange Multiplier (LM) test checks for first-order ARCH effects. Equation 2 shows the temporal dependence of the squared errors (t-statistics are in parentheses):

$$\hat{e}_t^2 = \underset{(4.56)}{.002} + \underset{(2.34)}{.21\hat{e}_{t-1}^2}, \tag{2}$$

where adjusted R^2 = .04 log likelihood = 481.38. The LM test for the first-order ARCH is $N \times R^2$ and is distributed as a chi-square with one degree of freedom. The computed value from Equation 2 is 5.36, which is significant at the 0.05 level. Tests for higher-order ARCH failed to find any further pattern in the conditional variance. The fact that higher-order ARCH tests yield insignificant results indicates that a simple ARCH(1) correction is appropriate.

To correct for the conditional heteroskedasticity in the data, we reestimate Equation 1 as an ARCH(1) process. A FORTRAN program called GARCH, which uses the Berndt et al. (1974) algorithm, jointly estimates the time-series model for GY and the time-varying conditional variance equation:

$$GY_t = \underset{(8.44)}{.04} - \underset{(-1.97)}{.38AR(1)} + \underset{(2.84)}{.56MA(1)} + \underset{(2.10)}{.15MA(2)} + \underset{(2.27)}{.08W4246_t} \tag{3}$$

$$\sigma_{\epsilon t}^2 = \underset{(4.22)}{.001} + \underset{(3.02)}{.74e_{t-1}^2}, \tag{4}$$

where log likelihood = 192.74, Ljung-Box Q-statistic levels (6 lags) = 4.65 and squares (6 lags) = 5.35, and Jarque-Bera statistic = 1.37. Equation (4) demonstrates the existence of strong ARCH effects. The coefficient on the ARCH term is significant at the 0.01 level, and its value is 0.74, which indicates that the conditional variance is stationary. Furthermore, the Ljung-Box Q-test statistics for the standardized residuals and the standardized squared residuals reject any further first- or second-order serial dependence. The Jarque-Bera statistic of 1.37 fails to reject normally distributed errors.

Next, we test whether the conditional volatility of output growth significantly affects its growth rate by estimating an ARCH(1)-M model:

$$GY_t = \underset{(0.88)}{.01} - \underset{(-2.66)}{.41AR(1)} + \underset{(5.19)}{.68MA(1)} + \underset{(4.93)}{.30MA(2)} + \underset{(0.49)}{.001W4246_t} + \underset{(3.29)}{.69\sigma_{\epsilon t}} \tag{5}$$

$$\sigma_{\epsilon t}^2 = \underset{(2.83)}{.001} + \underset{(2.99)}{.89e_{t-1}^2}, \tag{6}$$

where log likelihood = 195.67, Ljung-Box Q-statistic levels (6 lags) = 5.29 and squares (6 lags) = 5.67, and Jarque-Bera statistic = 3.37. The results show that the conditional standard deviation of output significantly increases its growth rate. The coefficient of the conditional standard deviation ($\sigma_{\epsilon t}$) in the output equation is positive and significant at the 0.01 level. This result is consistent with Mirman's (1971) and Black's (1987) hypotheses

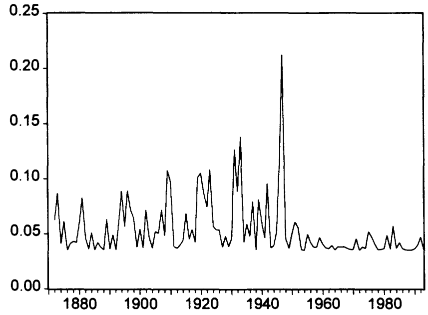

Figure 2. Conditional Standard Deviation of Output Growth

and the previous empirical findings of Kormendi and Meguire (1985) and Grier and Tullock (1989).

The sample period includes a few calamitous episodes in U.S. economic history, the most serious of which is the Great Depression. An appropriate test of the robustness of the model is to exclude the volatile 1930s and reestimate the system over more normal conditions. We created the dummy variable DUM2938, which has a value of one during the years 1929–1938. These dates were chosen because the Depression began in the summer of 1929, and it was not until 1939 that real GNP regained and then exceeded its 1929 level. The results presented below show that the conditional standard deviation of output significantly increases growth even when the Depression years are excluded.

$$\begin{aligned} \mathrm{GY}_t = \underset{(1.11)}{.01} - \underset{(-2.59)}{.43\mathrm{AR}(1)} + \underset{(4.35)}{.65\mathrm{MA}(1)} + \underset{(3.99)}{.26\mathrm{MA}(2)} + \underset{(0.11)}{.001\mathrm{W4246}_t} \\ - \underset{(-1.70)}{.02\mathrm{DUM2938}} + \underset{(3.07)}{.68\sigma_{\epsilon t}} \end{aligned} \tag{7}$$

$$\sigma^2_{\epsilon t} = \underset{(2.94)}{.001} + \underset{(2.95)}{.84e^2_{t-1}}, \tag{8}$$

where log likelihood = 196.57, Ljung-Box Q-statistic levels (6 lags) = 6.52 and squares (6 lags) = 7.63, and Jarque-Bera statistic = 0.45.

4. Further Evidence

In the systems outlined in Equations 5 through 8, output uncertainty and its effect on growth are estimated simultaneously. Furthermore, the ARCH-M model yields consistent estimation. However, variability is constrained to contemporaneously affect output growth; therefore, the model does not allow us to evaluate the relationship between variability and growth over time. In this section, we use a different approach—impulse response functions—to reveal the interaction between growth and variability through time. A problem with this technique is that it forces us to use a two-stage process with a generated regressor in the second stage (for a discussion, see Pagan 1984).[4]

[4] We use generated regressors to analyze lagged effects because we are unable to model simultaneously an ARCH-M system with lags of the conditional variance.

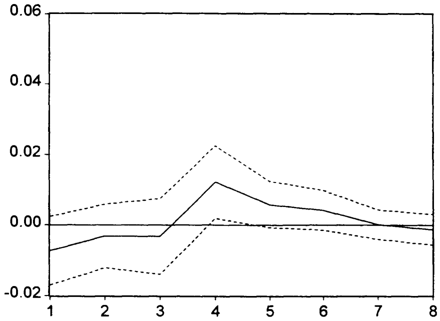

Figure 3. Response of Output Growth to a One-Standard-Deviation Shock to Its Conditional Standard Deviation (Standard Error Bounds Computed Using Monte Carlo Simulations; 1,000 Repetitions)

First, we generate a consistent estimate of the conditional standard deviation of output growth using the predicted value from Equation 4. The series is presented in Figure 2. Second, we estimate the following two-variable vector autoregression:

$$[\text{GY}, \sigma_\epsilon], \tag{9}$$

where σ_ϵ is the conditional standard deviation of output growth. The World War II dummy (W4246) is included as an exogenous variable. A lag length of 3 is chosen because it minimizes the Schwartz and Akaike information criteria. In the equation with GY as the dependent variable, the first 2 lags of σ_ϵ are negative and insignificant, whereas the third is large, positive, and significant. Therefore, the sum of the coefficients of the lags is positive. The conditional standard deviation of output growth Granger causes output growth; an F-statistic of 2.72 was obtained, which is significant at the 0.05 level.

Figure 3 graphs the impulse response function associated with a one-standard-deviation shock in σ_ϵ.[5] Output growth is at first somewhat negative but then responds in a strongly positive direction to the shock after three years.[6] It reaches its peak after four years, then declines but still has a cumulative positive impact until the seventh year. This unearthed lag structure between variability and growth is consistent with Black's hypothesis: The technologies that agents are choosing in response to a risk-return trade-off take time to yield output changes and then to die out. In addition, the results are consistent with Mirman's hypothesis, which deals with the long-run effects of savings on growth.

5. Concluding Remarks

Using a long time series, we estimate an ARCH-M model to analyze the relationship between the conditional standard deviation of real GNP and its growth rate. We find that variability significantly increases output growth rates. These results support the theoretical work of

[5] The impulse response functions were calculated using a Choleski Decomposition in which output growth was ordered before its conditional standard deviation.

[6] This result does not conflict with our earlier finding of a positive relationship between the conditional variability of output and growth; the ARCH-M model includes contemporaneous variability, whereas the vector autoregression contains lags.

Black (1987) and Mirman (1971) and are consistent with the empirical studies of Kormendi and Meguire (1985) and Grier and Tullock (1989).

Our results are counter to those of Zarnowitz and Moore (1986) and Ramey and Ramey (1991). Zarnowitz and Moore use a nonparametric approach, whereas an ARCH-M system allows us to formally test hypotheses concerning the influence of variability on growth. In contrast to Ramey and Ramey, we use a long time series, whereas they use a large sample of countries. Also, our methodologies differ greatly. The results of Ramey and Ramey in particular suggest that further work be done to apply this model to different countries to test the robustness of our results.

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